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# Psychological characteristics of students taking programming-oriented and applications-oriented computing courses

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# Psychological Characteristics of Students Taking Programming-Oriented and Applications-Oriented Computing Courses

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## ABSTRACT

The characteristics of students taking programming-oriented and applications-oriented higher education courses are compared. Relative to the latter students, the former students' personalities are shown to be of a more schizoid nature, this providing an explanation of these students' greater computer engagement, programming experience and computing aptitude, at least as far as males are concerned. The extent to which programming experience is accumulated by females is concluded to be a major factor explaining the greater gender imbalance in enrolment on the programming-oriented course.

Psychometric measures are found to be useful over and above cheaper, more easily obtainable, information in discriminating between the two types of student. However, psychometric measures are not found useful in increasing the association between correctness of course classification subsequent to Discriminant Function Analysis and success/failure on the courses.

Finally, the same set of characteristics, involving among other things, greater involvement in computing, is found to be associated with success irrespective of course.

## INTRODUCTION

Much has been written on gender differences concerning participation in programming-oriented and applications-oriented computing activities [1,2,3,4,5,6]. However, there have been few investigations of other psychological factors which might explain why individuals are differentially drawn towards these two areas of computing. From a theoretical standpoint, such studies are useful in testing psychological theory and in advancing the work on gender differences. In a more applied vein, such research is potentially useful in providing pointers to computing tutors asked for advice by aspiring students unsure of which type of computing course they should follow, and also in helping reduce institutional financial losses associated with course wastage rates. With respect to this latter point, it can be calculated that, on average, the loss in fees attributable to student dropout / failure for the two courses considered in the present study amounts to the equivalent of $437,286 per yearly intake. There is therefore considerable incentive to investigate ways in which such losses can be ameliorated.

The present study aimed to assess whether certain characteristics distinguish students taking programming-oriented and applications-oriented computing courses. Also investigated was the matter of whether students whose profiles were more typical of students taking the type of course other than that actually studied were less likely to successfully complete courses than those possessing characteristics similar to their course colleagues. Towards these ends, students enrolling in higher education Computing (programming-oriented) and Business Information Technology (BIT - applications-oriented) courses were contrasted.

One of the main distinctions which can be drawn between the nature of programming and applications courses concerns a focus upon computing itself as compared with the use of computing as a tool used towards other ends [1]. Given this, and the likelihood that, because of its computing-centered nature, more highly computer involved individuals would enroll in the Computing course, much of the rationale for the present study stemmed from the assumption that students taking the Computing and BIT courses would be more and less akin to Shotton's [7] computer dependents respectively. Hence, the first factor considered as possibly differentiating the two types of student was computer engagement as measured by the Computer Apathy and Anxiety Scale [8]. Here, individuals are placed along a continuum running from extreme apathy towards computer usage at one end, to a great desire to use computers at the other. Further justification for the idea of greater Computing student computer engagement came from work on graduate business administration students, showing increasing importance of computing in a person's life to be positively related to previous programming experience, but not to previous applications experience [9]. It is important to differentiate the concept of high computer engagement from computer addiction. While both high engagement and addiction imply a high degree of computer usage and involvement, the former is not conceived by the current authors as being pathological (i.e. it does not have negative consequences for the individual, whereas the latter does). In this respect, high computer engagement is considered to be broadly similar to Shotton's conception of computer dependency, however the term "dependency" denotes some form of reliance [10], therefore the present authors prefer to avoid usage of this term.

It was further assumed that the Computing course, with its emphasis on programming (an activity often associated with mathematics - [11]), would be more likely to appeal to individuals with a liking for sciences. On the other hand, the assumption was made that the BIT course, with its emphasis on applying computers to business problems, would be more attractive to individuals with a greater orientation towards business and the arts. Here, work from the 1960s showed programmers employed in scientific domains to be highly interested in scientific and aesthetic issues, but programmers employed in more business-oriented spheres to be more interested in business issues [12]. Thus, while these observations concerned programmers, this supports the suggestion that individuals interested in business computing are not highly oriented towards science. All this led to the inclusion of number of arts and science subjects previously studied as possible distinguishing variables in the study.

The arts/science dichotomy also suggested other differences, psychologists having previously proposed many cognitive and personality differences between individuals differing in arts/science orientation. For example, the 16 Personality Factor Questionnaire (16PF), a commonly used measure of normal (i.e. non-clinical) personality traits, often reveals undergraduates studying arts and sciences to be relatively tender-minded and tough-minded respectively [13,14] (tender-minded individuals are relatively emotionally sensitive, optimistic, insecure and display a preference for reason over force [10,15], while tough-minded individuals are typically self-reliant and materialistic [10,16]). Also, scientists tend to have theoretical and economic values, whereas arts specialists tend to have aesthetic and social values [14]. Consistent with all this, individuals scoring low on the 16PF second-order tough-poise factor are characterized as being warm, sentimental and having a liking for drama and art, while individuals scoring high on this factor are characterized as alert, realistic, practical and as keeping their feelings under control [16]. (Note that, according to Cattell, the 16 primary factors measured by the 16PF provide a detailed measure of the whole of the normal personality sphere. These primary factors, which are inter-correlated, can be combined into five broader second-order factors using equations involving sums of primary factors' weighted scores. The primary tender-minded – tough-minded dimension is highly implicated in calculation of the second-order tough-poise factor.)

The above paints science-oriented individuals as less socially inclined than those with a bent towards the arts, and this is supported by findings showing programmers to be object-centered, rather than person-centered [12]. Research also shows that programmers and individuals in allied occupations such as systems analysts tend towards introversion [17]. Additionally, Shotton's work on computer dependent individuals concluded that such individuals are likely to be introverted, possibly viewing the computer as a friend, rather than simply as a tool [7]. For such reasons, she cited introversion as a likely major reason as to why her computer dependents became involved with computers. So, the more scientific, programming-oriented, nature of the Computing course, led to the assumption that Computing students should exhibit greater introversion than BIT students.

The previously mentioned portraits of arts-oriented and science-oriented individuals as tender-minded and tough-minded respectively are also consistent with findings of high tough-poise in computer dependents, such individuals also exhibiting highly independent personalities [7], this latter second-order 16PF dimension contrasting radical, strong self-willed (independent) individuals with those of a more subdued nature [18]. These observations suggested the hypotheses that Computing students should be more independent, and higher in tough-poise than BIT students.

Together, the introverted, independent and non-emotional (high tough-poise) personality characteristics of Shotton's computer dependents constituted schizoid personalities (the term schizoid should not be confused with schizophrenic, in contrast to the latter, the former does not imply any kind of clinical problem, but simply denotes a type of individual who dissociates emotional from intellectual considerations [7]). The schizoid individual's eschewing of personal relationships and emotional involvement leads to greater absorption in intellectual matters, intellectual arguments often being used as a form a defense in emotional situations. We might therefore expect schizoid individuals to have sharply honed intellectual skills, and indeed Shotton's computer dependents were found to be highly intelligent [7]. From this, it will be apparent that Computing students were expected to outperform BIT students on the intellectual measure used in the present study.

Among the explanations forwarded for the previously mentioned individual differences in personality are neurophysiological theories (e.g. Eysenck's theory of introversion-extraversion [19]) and psychoanalytic theories (e.g. the idea that computer dependents' schizoid personalities are attributable to insecurity resulting from parental affection being contingent upon achievement [7]). However, detailed consideration of the etiology of differences presently considered lies beyond the scope of this paper.

Two final factors considered in the study were computing experience and gender. Firstly, because of the differing emphases of the two courses, it was expected that Computing and BIT students would have previously used greater numbers of programming languages and applications packages respectively.

A large gender imbalance favoring males is usually found for programming courses, the imbalance being much reduced or even reversed to some extent for applications courses [2,3,5]. Thus, it has been concluded that females might not avoid computers *per se*, but rather that they might avoid specializing in computing [3]. This situation has been attributed to social conditioning and the negative evaluation of programming because of its perceived connection with mathematics [20,21,22]. Such factors are among those which have been cited as responsible for the “we can, but I can't” paradox: females' perceptions that while they lack the competence themselves to study programming, this does not apply to females generally [e.g. 2]. Additionally, using computers as general-purpose information processing tools is often looked upon more favorably by females than using computers for exclusively computing-related purposes, since they see such usage as equipping them with useful skills for the future [1]. Finally, schizoid personality characteristics, which we have previously associated with high computer engagement/dependency, are found more often in males than females [7]. For all these reasons the literature suggested that gender would be a useful indicator of course membership in the present study, it being expected that the gender imbalance favoring males would be greater for the Computing course than for the BIT course.

A last point to note is that, from a practical point of view, it was useful to contrast the classificatory utility of biographical and attitudinal data which was easy and cheap to obtain with that of less convenient and more expensive psychometric personality and aptitudinal measures. This aspect of the study took note of comments recognizing that the use of time consuming measures in advising students as to choice of computing courses is often unrealistic for the purposes of giving day-to-day advice [23]. Hence, a two stage analytical procedure was adopted, testing whether psychometric measures offered any utility over and above biographical and attitudinal data in classifying students as to course membership. The utility of the classification schemes was then tested by relating correctness of classification to success/failure in obtaining qualifications.

## METHOD

### *Design*

The main part of the study tested whether a combination of certain variables could be usefully used to classify students according to course. Towards this end, hierarchical Discriminant Function Analysis (DFA) was used, gender, computer engagement score, number of programming languages and applications packages previously used, number of arts GCSEs and number of science GCSEs being entered at a first stage (GCSEs are certificates awarded in the UK at age 16 on the completion of compulsory education). At a second stage, computing aptitude and extraversion were entered as further independent variables in the prediction of the course membership (Computing versus BIT) dependent variable.

Subsequent to the above, the utility of the classificatory scheme was assessed by testing whether students mis-classified by the DFA had a greater tendency to be unsuccessful than those correctly classified. Here, analyses were performed for the Computing and BIT students and both stages of the DFA separately. Hence, four 2x2 chi-square tests of association were performed in analyses where Classification (correct or incorrect) and Outcome (success or failure in obtaining the course qualification) were the variables of interest.

It was not reasonable to include tough-poise and independence in the DFA since these 16PF second-order factors are not statistically independent of extraversion (they are calculated from the same primary data). Therefore two independent samples t-tests were conducted to test the hypotheses involving the independence and tough-poise data.

*Respondents*

Data was acquired from two years' intakes of the Higher National Diploma (HND) Computing and BIT courses run by Bolton Institute (HNDs are sub-degree, vocationally-oriented, qualifications awarded in the UK).

There were 69 males and 10 females enrolling in the Computing course. Of these, 54 (68% - 46 males and 8 females) yielded full data sets. These students were in the age range 18 - 44 (mean= 21.94 years, SD=5.51 years).

Of the 39 males and 25 females enrolling in the BIT course, 42 (66%), provided full data sets (24 males and 18 females). Here, ages ranged from 18 to 51 (mean=22.17 years, SD=7.98 years).

Students yielding full data sets were found to be representative of the course intakes in terms of gender balance and age.

*Materials*

Information on gender, number of programming languages and applications packages previously used, and number of arts and science GCSEs was collected by means of a biographical questionnaire. Computer engagement data was collected using the Computer Apathy and Anxiety Scale (CAAS - [8]). This data consisted of reversed polarity scores on the Engagement-Apathy subscale, higher scores indicating greater computer engagement.

Aptitude and personality data were obtained by means of the Computer Programmer Aptitude Battery (CPAB - [24]) and the 16PF [18] respectively.

The CPAB was used in place of a more general measure of intellectual aptitude because of its usefulness within the wider context of the research program of which the present study was part. Use of the CPAB as an indicator of general academic aptitude was justified since the manual reveals CPAB performance to be highly correlated with that on the Thurstone Test of Mental Alertness [24], which has been categorized as a test of academic intelligence [25]. Indeed, on balance, the manual shows the CPAB – Thurstone relationship to be greater than that between CPAB scores and those on the IBM Programmer Aptitude Test.

All three personality indices considered were second-order 16PF factors. Since it was desirable to calculate both sexes' second-order 16PF indices from the same equations, extraversion was calculated using the sexes combined equation of Krug and Johns [26]. However, it was necessary to use the older equations of Cattell and colleagues [18] for calculation of the independence and tough-poise indices, since Krug and Johns did not provide equations for the sexes combined for these factors. High scores on the personality factors indicated increasing extraversion, independence and tough-poise respectively.

*Brief Descriptions of Courses*

Educational qualifications required for entry to the two courses were identical. Each course lasted for two years, assessment being by coursework and examination.

The Computing course emphasized the process of computing itself (for example, the course included training in C++ and COBOL programming, systems analysis and design, and computer systems architecture). This course aimed to equip students with the skills needed to obtain employment as computer programmers, programmer analysts or systems analysts.

The BIT course emphasized the applications to which computers can be put (including training in data processing and information systems, business operations and environments, the development of business systems and the use of software packages). This course aimed to train students to develop, monitor and support applications of information technology in business environments, in order to gain employment in areas such as end-user support, installation and support of computer packages on networks, and development of office automation.

### *Procedure*

In the final month before the start of the courses, students were mailed copies of the CAAS and biographical questionnaire, and asked to return these by reply-paid post.

Administration of the CPAB and 16PF took place during induction weeks, students taking each course completing the instruments in different testing sessions. The instruments were administered according to the instructions provided in the manuals, and on different days in order to avoid student fatigue.

## RESULTS

Discriminant Function Analysis

Using Wilks' lambda as a basis for obtaining F values, the six predictors in the first stage of the DFA (number of arts GCSEs, number of science GCSEs, gender, computer engagement score, number of programming languages previously used, and number of applications packages previously used) enabled a significant separation of the two courses ($F_{6,89}$=5.642, p=.0001). With prior probabilities calculated according to sample sizes, 67.71% of students were correctly classified as to their course membership (see Table 1). This result was roughly 17 percentage points better than the approximate 51% correct classification rate expected by chance.

------- INSERT TABLE 1 HERE -------

Subsequent to the second stage of the DFA, with computing aptitude and extraversion also entered, separation of groups was again significant ($F_{8,87}$=5.20, p<.0001). Here, 78.13% of cases were correctly classified (see Table 2), this being around 27 percentage points greater than the approximate 51% chance level..

------- INSERT TABLE 2 HERE -------

McNemar's repeated-measures chi-square test for cases changing in correctness of classification between the DFA's two stages [27] showed that the approximate 10 percentage point increase in correct classification resulting from the addition of the psychometric data in stage two constituted a significant improvement on the number of correct classifications yielded by stage one (chi-square=5.05, df=1, p<.05).

------- INSERT TABLE 3 HERE -------

Considering only loadings in excess of +/-0.33 to interpret functions [27], correlations between predictors and the discriminant function obtained (see Table 3), showed that number of programming languages previously used, followed (in descending order of magnitude) by gender, aptitude, computer engagement, number of Arts GCSEs and extraversion were the most useful variables differentiating the Computing and BIT students. Number of Science GCSEs and number of applications packages previously used were not particularly useful in predicting group membership. The univariate F statistics reflected this situation, the latter two variables being the only two upon which the two groups did not significantly differ.

The means in Table 4 show that, relative to BIT students, Computing students had experience of using more programming languages, had greater computing aptitude, were more engaged with computers, had fewer Arts GCSEs, and were more introverted, all these differences being as predicted. Note that, while the two groups did not differ significantly on applications package usage, the difference in means was in the opposite direction to that predicted, Computing students' usage being higher.

------- INSERT TABLE 4 HERE -------

The significant univariate F for gender reflected the greater imbalance, favoring males, in the Computing group (85.2% versus 14.8%) as compared to that in the BIT group (57.1% versus 42.9%).

The second set of F statistics in Table 3 show that with all other independent variables controlled, and alpha set at 0.005 to control Type I error rate, no single variable made a significantly unique contribution in distinguishing between the groups.

The Association Between Classification and Performance

In testing whether correctly classified students were more likely to be successful than those classified incorrectly, final year referrals and deferrals were excluded from analyses because of uncertainty as to their success/failure, hence the slightly lower sample sizes compared to the DFA.

*Classification and Performance of Computing Students*

The chi-square contingency tables for analyses based upon classifications for Computing students subsequent to the first and second stages of the DFA are presented as Tables 5 and 6. The values of chi-square associated with these contingency tables were 5.12 (df=1, p<.05) and 5.08 (df=1, p<.05) respectively. (The sample size in Table 6 was high enough for the low expected frequency in the Incorrect-HND cell to be unproblematic [28].)

------- INSERT TABLE 5 HERE -------

Comparison of observed and expected frequencies results in the conclusion that for both stages there were significant associations, whereby, as hypothesized, Computing students incorrectly classified as BIT students were more likely to fail to obtain an HND than those correctly classified . Note that the utility of the classification function resulting from stage two, where *more* information was used, was slightly *worse* than that resulting from stage one.

------- INSERT TABLE 6 HERE -------

*Classification and Performance of BIT Students*

The directions of the differences in observed and expected frequencies in the two chi-square analyses for BIT students were directly opposed to those for the Computing students reported above, it being evident from Tables 7 and 8 that, if anything, mis-classification was associated with achieving the HND qualification. Here, the association was significant for the first stage of the DFA (chi-square=5.30, df=1, $p<.05$), but not the second stage (chi-square=1.81, df=1, $p>.05$).

------- INSERT TABLE 7 HERE -------

------- INSERT TABLE 8 HERE -------

Contrary to the hypothesis then, mis-classification of BIT students as Computing students tended to be associated with success on the BIT course, the association being significant for classifications based upon DFA stage one, but not stage two.

Personality Differences not Included in the DFA

For hypotheses tested outside the DFA, Course (Computing versus BIT) served as an independent variable in separate independent samples t-tests where tough-poise and independence were dependent variables.

------- INSERT TABLE 9 HERE -------

Reference to the means and t-test results in Table 9 shows that Computing students exhibited significantly greater independence, the corresponding hypothesis thus being supported.

While, as was hypothesized, the tough-poise mean for Computing students was greater than that for BIT students, the difference between the means was non-significant. Therefore it was concluded that support for this hypothesis was inadequate.

## DISCUSSION

From a theoretical perspective, one of the most interesting findings of the present study revolved around confirmation of the idea that, relative to non-programming-oriented students, programming-oriented students exhibit more schizoid personalities, in terms of greater introversion and (for males at least) independence. This portrays the former individuals as relatively aloof, having a tendency to plough their own furrow in life. However, with respect to the suggested lesser emotionality of the Computing students, the evidence was insubstantial as far as differences in the schizoid characteristic of tough-poise were concerned.

The finding for introversion was consistent with the idea that the Computing students were more likely to have object-centered, rather than person-centered, interests. It is this which is likely to explain their greater computer involvement, as indicated by their greater computer engagement and programming experience. (This greater involvement though, did not extend to greater applications experience where no difference was identified. Because of the nature of their course, BIT students were hypothesized as having the advantage here. However, the fact that greater BIT student experience was not present in an area of computing where this might have been expected, adds some support to the notion that Computing students were more computer involved.)

With the exception of the null tough-poise result, the present link between schizoid personality traits and computer involvement supports Shotton's findings for her computer dependents [7]. While schizoid characteristics are typical of science-oriented individuals more generally, present findings concerning previous academic study were only partially consistent with this, and with the assumption that Computing and BIT students would be more science-oriented and arts-oriented respectively. Here, while Computing students had studied fewer arts disciplines, there was no reliable difference in number of science disciplines previously studied, albeit that the difference in means was in the predicted direction.

In addition to explaining their greater computer involvement, the schizoid characteristics of the

Computing students also explain these students' superior aptitude test performance, these less outgoing individuals' intellectual skills being better developed by virtue of the greater emphasis they place on intellectual considerations at the expense of social considerations.

From an applied perspective, it was found possible to distinguish between members of the two courses using easily obtainable information: as discussed above, members of the Computing course had previously used a greater number of computer programming languages, were more highly computer engaged and had fewer arts GCSEs, these students were also more likely to be male. Introduction of psychometric data allowed an even clearer distinction to be drawn, Computing students having better computing aptitude and being more introverted. *En masse*, these distinctions were found to be useful in predicting which students would ultimately obtain the HND qualification. But instead of students correctly classified as belonging to the Computing and BIT courses being more likely to receive their respective HNDs than those incorrectly classified, as was originally envisaged, it was students who were classified as being members of the Computing course, irrespective of whether this was true, who were proportionately more likely to obtain their award. Given that addition of the more expensive aptitudinal and personality data did not increase the utility of the DFA classification process as a predictor of course outcomes, one reason why BIT students mis-classified as belonging to the Computing course fared better than their correctly classified colleagues appears to have been their greater computer involvement (high engagement and greater programming experience). Hence, it seems as though degree of immersion in the computing culture was particularly important in determining success across the two courses.

The fact that gender was a predictor of course membership is consistent with findings of greater female take-up of applications-oriented than programming-oriented courses, resulting from females' interest in computers as information processing tools rather than being interested in computing as an end in itself [1,3]. In the present study there were more than seven times as many males as females taking the Computing course, but only one and a half times as many males taking the BIT course. The fact that the BIT course contained some technically-oriented components, such as the setting-up and maintenance of networks, probably explains why, while the imbalance in favor of males was diminished, the gender asymmetry was nevertheless substantial. Note also that this more technical content of the BIT course probably explains why BIT students incorrectly classified as Computing students (and who were more computer involved than their course colleagues) performed particularly well on the BIT course.

The DFA statistics showed Gender as having the second highest univariate F. However, controlling for other variables resulted in a large drop in F, the adjusted F value for Gender being the second lowest value. This suggests that gender differences on other variables carry most of the discriminatory information afforded by explicitly including gender in an analysis of this type. Indeed, classification statistics for an informal seven variable DFA excluding gender as an independent variable (not shown) were the same in all respects as those for the eight variable DFA reported.

The observation that variables other than gender are capable of explaining gender differences in course enrollment implies that the potentially controversial step of including gender in a predictive formula for advising students as to course choice is avoidable. On the other hand, though politically more acceptable, using all the other independent variables considered in the analysis apart from gender would still perpetuate gender differences in course membership since gender would obviously be a covariate.

It would have been useful to be able to compare females enrolling upon the Computing and BIT courses as a means towards identifying reasons for the greater gender imbalance on the former course. But, unfortunately, this very imbalance meant that the Computing female cohort was too small for any significant results to be yielded. For example, while differences in female Computing and BIT student means for extraversion, engagement and number of arts GCSEs studied were consistent with and bigger than those for the Computing and BIT groups overall, 95% confidence intervals for these means were found to overlap. Though slightly diminished, inter-female differences in means for number of programming languages, number of applications packages previously used and number of science GCSEs taken were also in the same direction as the overall group differences. Given these observations, some speculative discussion is useful. (Gender-specific descriptive statistics are provided in an appendix.)

Although the difference in programming experience between females taking the two courses was smaller than the overall difference across the courses as a whole, it is important to observe that the majority of BIT females (77.3%) had no programming experience, whereas Computing females having no programming experience were in the minority (37.5%). Together with greater Computing female computer engagement, this suggests that, on the whole, Computing females were likely to be more deeply involved in the computer culture than BIT females: programming is a computing activity which is at a more profound level than the learning and use of most applications packages, and it should be noted that the difference in number of applications packages previously used by females taking the two courses was minimal. Such differences are likely to have played a major part in females' course choice.

Despite our previous emphasis upon the schizoid personality construct as a major explanation of differences between students taking the two courses, it appears that such considerations might apply primarily to the males constituting the majority on each course. For females, while Computing students were more introverted than BIT females, they did not exhibit greater independence or tough-poise (both stereotypically masculine traits [16,29,30]). So, Computing females did not appear to possess personality traits associated with the greater social confidence which might be suspected characteristic of females enrolling on a course involving stereotypically male subject matter and where females are in a small minority. While such an idea is intuitively appealing then, on the present limited data, there appears to be no evidence that greater social confidence allowed Computing females to become exceptions to the “we can, but I can't” phenomenon referred to by authors such as Chen [2].

Although Computing females displayed a greater depth of involvement in the computing culture, there was no strong evidence that they had a greater scientific bent in terms of number of science GCSEs studied, however, they were found to have studied fewer GCSE arts subjects.

Putting the findings on programming experience and the study of arts together, it is of course possible that BIT females' relative lack of programming experience and their preference for the BIT course over the Computing course, were not causally related (indeed, the correlational nature of the study means that it would be incorrect to infer causal explanations for any of the present results). Rather, given their greater propensity for studying more verbally oriented, less technical, disciplines, a common antecedent explanation of these females' course choice and lack of programming experience could be that they simply did not want to engage in programming. After all, we have previously noted that females are more likely than males to view computers as tools towards non-computing ends, rather than see computing as an end in itself [1]. In the terms of Temple and Lips [3] this would imply a Subjective Choice explanation of BIT females' course choice, involving their attraction away from programming-oriented computing towards areas they find more appealing, possibly because of social conditioning. This contrasts with an explanation concerning self-perceived deficiencies in experience and ability, resulting in the choice of an applications-oriented course (here we should note that, with respect to aptitude, BIT females' performance was actually stronger). Such a conclusion is also consistent with the suggestion of Durndell and colleagues that the “we can, but I can't” phenomenon be re-phrased “we can, but I don't want to” [31].

*Conclusions*

The present study shows that students taking programming-oriented and applications-oriented computing courses differ in a number of psychological characteristics, many of these, for males at least, being connected with a greater or lesser degree of schizoid demeanor. One suspects that the more schizoid, highly computer involved, students' relationships with computers and computing are often of a qualitatively different nature compared to the relationship enjoyed by other members of society. Glissov has already observed that his Computer Interested and Handy Persons appeared to be in a pleasurable, non-goal-oriented state while programming [32]. It would be interesting to see whether qualitative approaches such as personal construct technique [33] or discourse analysis [34], would be successful in elucidating the nature of other qualitative differences in the approach to computing of highly computer involved individuals relative to less involved individuals.

Despite attempts at rectifying the situation, there are still large gender imbalances in computing course enrollment, these being particularly pronounced for courses emphasizing programming. The fact that the picture with respect to course classification altered little when gender was not included as a discriminating variable, indicates that other variables presently considered, the most prominent of which is likely to be previous programming experience, are implicated in explaining gender differences in computing course choice. Structural equation modeling would constitute one possible way of disentangling the structure of relationships whereby gender and other factors interact in explaining differences in choice. Meanwhile, the present results suggest that gender asymmetries in programming-oriented higher education courses, and ultimately in programming-related employment, might be addressed by providing female schoolchildren with as much encouragement, and as many opportunities, as possible to engage in programming activities, so as to give those females who are interested in programming every chance of overcoming the cultural barriers which lie in their way. Also, granted the positive benefits which dissociating computing from mathematics seem to have (e.g. the work of Stockdale cited by Siann and colleagues [35]), it is probable that teaching of programming in a non-mathematical context would be particularly helpful in stimulating female interest. The preliminary evidence that Computing and BIT females differed little in terms of tough-poise and independence is important here, since if possession of a relatively masculine personality were a substantial reason as to why certain females accumulate more programming experience than others, then increasing female programming opportunities might have little effect in diminishing experiential gender imbalances. However, the present evidence suggests that this is not the case.

It was found possible to differentiate students taking the two courses according to their profiles on the variables considered, this being useful for descriptive and theoretical purposes. However, the aspect of the study which sought to provide information to assist tutors in their role as advisors to potential students as to type of course which might prove most suitable, was compromised by the observation that it was students classified as belonging to the Computing course who were more likely to succeed irrespective of course actually followed. Thus, the attributes associated with success were the same for both courses, depth of involvement in computing seeming to be an important factor here.

In practical terms then, assuming generalizability of the present results, it would seem possible to reduce student wastage on both types of course by taking into account the present biographical and attitudinal factors during the student recruitment process. If institutional loss of income resulting from withdrawing students' failure to take-up places in the second-year of the present courses alone is considered, rough calculations, involving both students who would have been incorrectly rejected and those who were incorrectly accepted according to the present classificatory results, reveal that a net institutional loss of the equivalent of $163, 525 would have been avoided. Although such a sum is obviously based upon statistics tailored to the present samples, and a certain amount of shrinkage would be expected for other samples, this emphasizes the important financial implications of the present type of work. Findings from further work identifying factors which are useful both in advising students whether to follow a programming-oriented or a non-programming-oriented course and at the same time predictive of success or failure on the course recommended, would obviously be more useful still. In the meantime, it is useful to bear in mind the observation that psychometric tests offered no advantage over and above biographical and attitudinal data in predicting student success (although such information was useful in distinguishing students opting for different types of course). Such a finding suggests that psychometric testing, and its associated logistical problems and financial costs, may be unnecessary in attempts to select students who will be ultimately successful on computing courses in general.

## APPENDIX 1

Gender-Specific Descriptive Statistics

------- INSERT APPENDIX 1a HERE -------

------- INSERT APPENDIX 1b HERE -------

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Table 1. Number and percentage of cases classified as belonging to each group after the initial stage of the DFA.

| | Predicted Group | |
|---|---|---|
| | Computing | BIT |
| Actual Group | | |
| Computing (n=54) | 39 (72.2%) | 15 (27.8%) |
| BIT (n=42) | 16 (38.1%) | 26 (61.9%) |

Table 2. Number and percentage of cases classified as belonging to each group after the second stage of the DFA.

| | Predicted Group | |
|---|---|---|
| | Computing | BIT |
| Actual Group | | |
| Computing (n=54) | 44 (81.5%) | 10 (18.5%) |
| BIT (n=42) | 11 (26.2%) | 31 (73.8%) |

Table 3. Correlations of variables with the discriminant function, and F statistics for group differences.

| Independent variable | Correlation with function | Univariate $F^a$ | $F^b$(other variables controlled) |
|---|---|---|---|
| Programming languages | 0.682 | $20.92^{***}$ | 9.15 |
| Gender | 0.476 | $10.21^{**}$ | 1.77 |
| Aptitude | 0.442 | $8.79^{**}$ | 1.93 |
| Engagement | 0.406 | $7.41^{**}$ | 1.58 |
| Arts GCSEs | -0.406 | $7.40^{**}$ | 1.99 |
| Extraversion | -0.375 | $6.31^{*}$ | 2.73 |
| Science GCSEs | 0.289 | 3.75 | 1.08 |
| Applications | 0.260 | 3.04 | 4.80 |

[a] Alpha=0.05 - $^{*}p<.025$, $^{**}p<.01$, $^{***}p<.001$ (df=1,94).

[b] Alpha=0.005 (see below) p>0.005 (df=1,86) in all cases.

Table 4. Raw score descriptive statistics for discriminating variables.

| Independent Variable | Computing (n=54) | | BIT (n=42) | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Programming language ($N_o$) | 2.13 | 1.80 | 0.71 | 0.99 |
| Aptitude (%) | 63.85 | 18.20 | 53.90 | 13.48 |
| Engagement (%) | 76.40 | 11.45 | 70.15 | 10.81 |
| Arts GCSEs ($N_o$) | 2.68 | 1.21 | 3.42 | 1.47 |
| Extraversion (Sten) | 5.48 | 1.90 | 6.53 | 2.18 |
| Science GCSEs ($N_o$) | 3.50 | 1.38 | 2.95 | 1.36 |
| Applications ($N_o$) | 6.63 | 4.78 | 5.02 | 4.62 |

Table 5. Contingency between Computing student classification and outcome for stage one of the DFA.

| | | CLASSIFICATION | | |
|---|---|---|---|---|
| | | Incorrect | Correct | Row Total |
| OUTCOME | No HND | Obs=10 (Exp=6.6) | Obs=16 (Exp=19.4) | 26 |
| | HND | Obs=2 (Exp=5.4) | Obs=19 (Exp=15.6) | 21 |
| | Column Total | 12 | 35 | N=47 |

Table 6. Contingency between Computing student classification and outcome for stage two of the DFA.

| | | CLASSIFICATION | | |
|---|---|---|---|---|
| | | Incorrect | Correct | Row Total |
| OUTCOME | No HND | Obs=8<br>(Exp=5) | Obs=18<br>(Exp=21) | 26 |
| | HND | Obs=1<br>(Exp=4) | Obs=20<br>(Exp=17) | 21 |
| | Column Total | 9 | 38 | N=47 |

Table 7. Contingency between BIT student classification and outcome for stage one of the DFA.

| | | CLASSIFICATION | | |
|---|---|---|---|---|
| | | Incorrect | Correct | Row Total |
| OUTCOME | No HND | Obs=5 (Exp=8.6) | Obs=17 (Exp=13.4) | 22 |
| | HND | Obs=11 (Exp=7.4) | Obs=8 (Exp=11.6) | 19 |
| | Column Total | 16 | 25 | N=41 |

Table 8. Contingency between BIT student classification and outcome for stage two of the DFA.

| | | CLASSIFICATION | | |
|---|---|---|---|---|
| | | Incorrect | Correct | Row Total |
| OUTCOME | No HND | Obs=4<br>(Exp=5.9) | Obs=18<br>(Exp=16.1) | 22 |
| | HND | Obs=7<br>(Exp=5.1) | Obs=12<br>(Exp=13.9) | 19 |
| | Column Total | 11 | 30 | N=41 |

Table 9. Independent t-test results for course differences on personality variables not included in the DFA (descriptive statistics are Sten scores).

| | Computing (n=54) | | BIT (n=42) | | t-test | |
|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | t | df |
| Tough-poise | 6.85 | 1.69 | 6.37 | 1.85 | 1.32 | 94 |
| Independence | 5.56 | 1.80 | 4.83 | 1.72 | 2.02* | 94 |

*p<.05 - one-tailed

Appendix 1a - Descriptive Statistics for Males

| | Computing (n=46) | | BIT (n=24) | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Programming languages ($N_o$) | 2.30 | 1.82 | 0.96 | 1.12 |
| Aptitude (%) | 67.22 | 16.80 | 54.63 | 11.70 |
| Engagement (%) | 77.22 | 11.84 | 72.95 | 10.40 |
| Arts GCSEs ($N_o$) | 2.65 | 1.06 | 2.96 | 1.40 |
| Extraversion (Sten) | 5.42 | 1.90 | 6.17 | 2.28 |
| Science GCSEs ($N_o$) | 3.50 | 1.39 | 2.75 | 1.48 |
| Applications ($N_o$) | 7.46 | 5.37 | 6.83 | 4.97 |
| Independence (Sten) | 5.81 | 1.74 | 5.09 | 1.83 |
| Tough-poise (Sten) | 7.08 | 1.61 | 6.75 | 1.88 |

Appendix 1b - Descriptive Statistics for Females

| | Computing (n=8) | | BIT (n=18) | |
|---|---|---|---|---|
| | Mean | SD | Mean | SD |
| Programming languages ($N_o$) | 1.13 | 1.36 | 0.39 | 0.70 |
| Aptitude (%) | 44.50 | 13.84 | 52.94 | 15.85 |
| Engagement (%) | 71.73 | 7.89 | 66.41 | 10.47 |
| Arts GCSEs ($N_o$) | 2.88 | 1.96 | 4.06 | 1.35 |
| Extraversion (Sten) | 5.83 | 2.02 | 7.00 | 1.99 |
| Science GCSEs ($N_o$) | 3.50 | 1.41 | 3.22 | 1.17 |
| Applications ($N_o$) | 3.13 | 2.42 | 2.61 | 2.70 |
| Independence (Sten) | 4.12 | 1.51 | 4.47 | 1.53 |
| Tough-poise (Sten) | 5.54 | 1.59 | 5.87 | 1.73 |